Contact-less Vital Parameter Determination: An e-Health Solution for Elderly Care

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Abstract: Vital parameters are key figures for the basis functions of the human body. Without these basis body functions, such as the heart beat, life is impossible. Therefore, vital parameters are indicators for a person's general medical condition. In recent years, the topic of vital parameter monitoring has been increasingly studied in the field of e-health. Especially the contact-less determination of vital parameters, such as heart rate, respiration rate, oxygen saturation and blood pressure, with consumer cameras brings a variety of advantages. In this work, we present methods to determine the mentioned vital parameters in a contact-less, optical way. Furthermore, we evaluated these methods for an utilisation in home environments with respect to elderly care. As a result, the remote determination of heart and respiration rate show reliable measurements, which makes the proposed methods ready for the application in home environments.

1 INTRODUCTION

e-Health has become an evolving field in recent years. The business consultancy Roland Berger expects that the e-health market will grow by 21 % every year (Berger et al., 2016). Thereby, e-health is a collective term for all applications of digital technology in the health care sector. That comprises electronic health records in the same way as telemedicine or consumer health informatics. Especially self-monitoring health care devices, such as fitness trackers, mobile apps, blood glucose monitors or blood pressure monitors, have shown to become of increasing interest in our society. The devices enable persons to analyse their own health status in an independent way.

However, all of these consumer products require body contact. This can be obstructive for persons with sensible skin and bears discomfort in wearing. Moreover, elderly people tend to forget to wear these devices because of dementia or other cognitive disabilities. In order to overcome these disadvantages, we propose to extract the vital parameters heart rate, respiration rate, oxygen saturation and blood pressure remotely in home environments. This vital parameter data can be recorded and analysed automatically. In case of emergencies, an alarm can be triggered. Moreover, the continuous monitoring can be a key element for an improved evidence-based diagnosis.

In this work, we want to outline the state of the art of remote vital parameter determination and present own methods to solve the research tasks. Hereby, we do not only carry out experiments in laboratory settings, but especially in realistic home environment scenarios. The aim is to investigate whether the single parameters can be measured accurately in the setting of home environments.

2 REMOTE HEART RATE DETERMINATION

2.1 Related Work

In the past, a human's heart rate was obtained by conventional methods such as the electrocardiogram or the photoplethysmography (PPG), which was proposed by Hertzman and Spealman (Hertzman and Spealman, 1937) and is based on determining the volumetric changes in the tissue optically.

By extending the original transmissive approach of the PPG, it is possible to determine the heart rate by reflective light (Humphreys et al., 2005). Verkruysse et al. continued with this idea and determi-

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ned the heart rate in the visible light spectrum by an RGB-camera (Verkruysse et al., 2008). The first automated approach in the visible light spectrum was proposed by Poh et al. (Poh et al., 2010). Further improvements consist in using temporal filters (van Gastel et al., 2014), autoregressive models (Tarassenko et al., 2014) or adaptive filtering (Wiede et al., 2016). This group of methods are considered as so-called intensity-based methods.

The other group of methods is called motion-based methods, because it makes use of small movements of the head that are caused by the heart bump induced blood flow according to the the 3rd Newtonian law. Balakrishnan et al. were the first to apply this principle (Balakrishnan et al., 2013) by tracking this motion with optical flow.

Nevertheless, all these methods do not eliminate the underlying artefacts or are not applicable for home environments.

2.2 Proposed Method

As outlined in the previous section, eliminating intensity and motion artefacts is the key factor for determining the heart rate robustly.

In the first step, a white balancing is necessary in order to compensate the differences in image acquisition of different cameras. For our implementation, we use the method presented by Garud et al. (Garud et al., 2014). In the next step, the face is detected within the image, because the face has both: A large amount of skin pixels and a good detectability with standard algorithms. We apply the face detector of Zhu and Ramanan (Zhu and Ramanan, 2012), because it not only provides the location of the image but as well its orientation based on facial landmarks. Afterwards, face regions with only skin, no hairs and less movements artefacts are selected, i. e. the forehead, the nose and the two cheeks. By transferring all pixels of these so-called regions of interest (ROI) to the HSV colour space, it is possible to determine an individual skin colour model for each person.

In the following, the video sequence can be continuously captured and the white balancing can be applied to each single image. The face can be tracked by a mixed approach of KLT tracking (Tomasi and Kanade, 1991) and tracking-by-detection. Subsequently, all pixels in the face matching the skin colour model criteria are extracted for the further processing. These extracted pixels are averaged in every time step for the three colour channels red, green and blue.

The three colour channels are normalised and bandpass filtered in order to exclude implausible frequencies. An independent component analysis (ICA) is applied to split the three filtered channels in one wanted signal and two noise signals. The result are three independent components. For each of them, the periodicity is calculated to determine the wanted signal component. For this component, the dominant frequency is computed by the Fast Fourier Transform (FFT) within a sliding window. This dominant frequency represents the heart rate. In order to prevent this algorithm from measuring sudden changes in the heart rate, an adaptive filtering is implemented as low-pass.

This algorithm shows an averaged root-mean-square error ($\overline{\text{RMSE}}$) ranging from 1.19 bumps per minute (BPM) to 2.93 BPM for selected lab scenarios (Wiede et al., 2018). These results have to be verified under realistic conditions in home environments.

2.3 Adjustments for Home Environment Measurements

Determining the heart rate in home environments holds some challenges in comparison to the laboratory scenarios. Normally, the cameras are fixed at the ceiling in home environments, so that they do not disturb the residents. On the one hand, a position at the ceiling is advantageous because of less occurring occlusion of objects and persons in the image. On the other hand, this is accompanied by a perspective viewpoint change, which leads to challenges in detecting a human's face. In Figure 1, such an example of perspective viewpoint change, with a very steep viewing angle can been seen.

Moreover, the distance to the camera is higher than in the lab scenarios. This goes hand in hand with a smaller spatial resolution, which means that the face is represented by less pixels. Furthermore, it cannot be guaranteed that a person is always upright in an image. Intensity artefacts strongly depend on the certain lighting in the room and can influence the measurements. In addition to that, motion artefacts occur during daily routines of the subject. To limit this challenge, we introduce the condition that measurements are only valid if the person sits or lies. If a person walks around, the uncertainty becomes too high, so that no measurements are taken.

The selection of the lens is crucial at this point. Whereas a narrow lens has less distortions and a high spatial resolution, it is necessary to place multiple cameras within one room for observation. In contrast to that, omnidirectional cameras are equipped with a fisheye lens, which enables to monitor the whole room with one camera. But fisheye lenses bear the problem of radial and tangential distortions. Furthermore, objects and persons are rotated in dependency

Figure 1: Different scenarios to determine the heart rate in home environments from left to right: Proband sits on a chair recorded by narrow lens camera, proband sits on a chair recorded by omnidirectional camera, proband lies in a bed recorded by monochromous camera.

of their position in the room, as can been seen in Figure 1. In order to overcome these issues and to still use omnidirectional cameras, we suggest to use a virtual perspective camera such as proposed by Meinel et al. (Meinel et al., 2014). This has the advantage that the rest of the algorithm can remain in its original form.

Another challenge we are facing is darkness such as in the night. Due to the fact that humans sleep a considerable time every day, we would loose a lot of information about vital parameters. In order to overcome this issue, we propose to perform the measurements in the IR-A light spectrum rather than in the visual light spectrum. To that goal, external LEDs in the near infra-red are applied. In Figure 1, such a monochromous image is shown while a proband lies in the bed. Furthermore, in the proposed algorithm we exclude the parts of skin colour determination, the ICA and the channel selection because we have one instead of three channels.

2.4 Results and Discussion

In order to evaluate whether the heart rate can be determined in home environments, different measurements were carried out.

Due the fact that the camera position strongly influences the viewing angle and the lighting conditions, different scenarios were taken into consideration, i. e. sitting on a chair or armchair and lying in a bed. The distance to the subjects varies from 1.5 m up to 4 m. In total, six probands were recruited for these three scenarios. All videos were recorded in a test flat at Chemnitz University of Technology to measure under realistic conditions. An Allied G201 RGB camera with a narrow lens was mounted on the ceiling for the measurements. For the infra-red measurements, an Allied Prosilica GM650 monochrome camera with external LED spotlights was used. Furthermore, the usage of omnidirectional cameras were evaluated. A Polar FT1 heart rate monitor was chosen as reference system. For a quantitative accuracy analysis, the root-mean-square error (RMSE) is chosen. The RMSE of different videos of the same scenario can be described by the mean $\overline{\text{RMSE}}$.

The results are summarised in Table 1. In the scenario sitting, the $\overline{\text{RMSE}}$ has a value of 1.9 BPM. The same value is obtained for the scenario lying in the bed. In the IR-A spectrum an $\overline{\text{RMSE}}$ of 2.6 BPM was attained for the heart rate determination. This value is worse in comparison to the value in the visual light spectrum. The reason for that can be found in the removal of the skin colour model and the ICA. However, this value is still accurate for the target application field. Moreover, it can be shown that a measurement of the heart rate with omnidirectional cameras is possible, but the value of the $\overline{\text{RMSE}}$ has increased because of the low spatial resolution.

Table 1: $\overline{\text{RMSE}}$ in BPM for different scenarios in home environments.

Scenario	$\overline{\text{RMSE}}$
Sitting	1.9
Lying	1.9
Lying (IR-A)	2.6
Omnidirectional camera	3.1

All results clearly indicate that the proposed optical heart rate determination method is suitable for usage in the field of home environments.

3 REMOTE RESPIRATION RATE DETERMINATION

3.1 Related Work

A second vital parameter of interest is the respiration rate. Pathological indicators of the respiration rate such as breathlessness and hyperventilation can be symptoms for several diseases. Conventional methods in clinical set-ups are for example respiratory effort belts, nasal thermistors or pressure transducers. However, all of these methods do not work contactless.

In this work, we want to focus on contact-less methods working in the visible light spectrum. A first approach was presented by Tan et al., which is based on edge detection and frame differencing (Tan et al., 2010). Other approaches make use of autoregressive models (Tarassenko et al., 2014) or use Eulerian video magnification (Sharma et al., 2015).

The largest group of methods is based on the principles of optical flow. On the basis of works of Nakajima et al. (Nakajima et al., 2001) and Frigola et al. (Frigola et al., 2002), Lukac et al. use a KLT tracking to determine the optical flow (Lukac et al., 2014).

3.2 Proposed Method

Based on the previous work by Wiede et al. (Wiede et al., 2017), a new algorithm was developed in the presented work. Firstly, images is acquired by an RGB or a monochrome camera. For the proposed algorithm it does not matter whether the images are coloured or grey value based, because our method relies on the lifting and lowering of the torso that is induced by the breathing.

In order to detect these torso motions, an ROI is placed in the image on the chest region. To that goal, we detect the face firstly. In comparison to Wiede et al. (Wiede et al., 2017), we suggest to use a face detector using the normalised pixel difference (Liao et al., 2016), which is by far more accurate. Based on the face region, we are able to determine the chest ROI. Subsequently, this ROI is split in four subregions of equal size.

In the next step, suitable features, in this case minimum Eigenvalue features (Shi and Tomasi, 1993), are detected in the subregions. The found feature points are tracked over time using the optical flow KLT method (Tomasi and Kanade, 1991). By observing the averaged motion of the feature points in each of the subregions, the y-trajectory can be extracted in a time channel. Only the y-component is considered in the following because it has the highest contribution in the breathing motion.

Thereupon, a bandpass filtering is performed to exclude implausible frequencies. In order to reject motion artefacts, a PCA is applied to the four filtered time channels of the subregions. In the following, the principal component with the highest spectrum density is considered as the wanted breathing signal. The final respiration rate is obtained from the dominant peak in the frequency spectrum computed with the FFT.

3.3 Adjustments for Home Environment Measurements

The problems that occur while determining the heart rate remotely in home environments (see 2.3) are the same as for the respiration rate. Especially the mounting of the camera on the ceiling is challenging because it influences the detection of the face and consequently the ROI selection. This issue can be overcome by using a face detector of Liao et al. (Liao et al., 2016), which can deal with large perspective distortions.

Avoiding motion artefacts while determining the respiration rate is more crucial than for the heart rate because the respiration rate algorithm is motion-based. Especially when breathing motion and arbitrary motion share the same frequency band, a clear determination is not always possible. For that reason, the influence of motion should be evaluated.

The possibilities of using omnidirectional cameras for respiration rate determination were investigated. For that, virtual perspective cameras, such as described in Section 2.3, were applied as well. A determination of the respiration rate during darkness did not require any changes in the algorithm because the method is motion-based. To carry out the image processing in the IR-A spectrum, only an external illumination was necessary.

3.4 Results and Discussion

The $\overline{\text{RMSE}}$ is used once more for the quantitative assessment. For the recordings in the visible light spectrum, a Basler acA640-100gc industrial camera and an Allied Prosilica GM650 monochrome camera in the IR-A spectrum were used. In total, four different scenarios with six probands were recorded in the test flat of Chemnitz University of Technology. As described in Section 2.4, we evaluate the scenarios sitting on chair or armchair, lying in the bed, during darkness and with an omnidirectional camera.

In order to have a reference for these estimated values, we developed an own reference system, which uses a piezo-electric transducer (MLT1132) to gather information about the chest movement. The data evaluation is processed on an STM32F401RE embedded board. Both the reference measurement and the video recording are carried out simultaneously.

The results for the home environment measurements are outlined in Table 2. It can been seen that the $\overline{\text{RMSE}}$ for sitting and lying is relatively small with 1.8 breaths per minute and 2.0 breaths per minute respectively. The differences might be explained by the different viewing angles. The $\overline{\text{RMSE}}$ for the IR-A spectrum is even lower than that. That could be due to the fact that the proposed method is motion-based and the probands performed less motion in darkness than during normal lighting conditions. We expected problems because of the thick blanket over the torso for the scenario lying in a bed, but this could not be confirmed. The usage of omnidirectional cameras was also successful for determining the respiration rate remotely. We could show that a virtual perspective camera can compensate the disadvantages of an omnirectional camera.

Table 2: $\overline{\text{RMSE}}$ in breaths per minute for different scenarios in home environments.

Scenario	$\overline{\text{RMSE}}$
Sitting	1.8
Lying	2.0
Lying (IR-A)	1.6
Omnidirectional camera	2.8

Under inclusion of all facts, there is evidence that the respiration rate can be determined accurately in home environments.

4 REMOTE OXYGEN SATURATION DETERMINATION

4.1 Related Work

The oxygen saturation in a clinical setting can be obtained by a pulsoximeter. This measurement device determines the absorption of light emitted by two LEDs of different wavelength and transmitted through thin body parts such as fingers or earlobes. By calculating the so-called ratio-of-ratios at the two wavelengths 660 nm and 940 nm for the oxygenated and deoxygenated haemoglobin, the oxygen saturation can be determined.

The basic concept of using one RGB camera to determine the oxygen saturation remotely was presented by Wieringa et al. (Wieringa et al., 2005). Tarassenko et al. used this preliminary work to determine the oxygen saturation by taking the red and blue channel of the camera instead of taking only a small bandwidth (Tarassenko et al., 2014). Subsequently, the AC- and DC-parts were determined. Guazzi et al. adapted this approach and only considered regions in the face that have a high signal-to-noise ratio (Guazzi et al., 2015). Alternatively, the oxygen saturation can be determined by a modulation of the reflected light (de Haan and Rocque, 2015).

In contrast to that, there exists the possibility to use two cameras in combination with optical bandpass filters, such as proposed by Kong et al. (Kong et al., 2013). This approach has the advantage of a small bandwidth, but needs to match in both of the images to analyse the same region. Verkruysse et al. suggested to choose rather one passband of the bandpass filters in the infra-red spectrum than in the visible light (Verkruysse et al., 2017).

Another method is considered as an active approach because it uses LEDs of different wavelengths to compute the oxygen saturation (Tsai et al., 2014).

Heretofore, all of the presented methods only operate under controlled environments in lab settings with fixed probands that are not moving and an active lighting.

4.2 Proposed Method

In a first setup, only one camera was used. Based on the red and the blue channel of a tracked ROI, we determined the AC- and DC-parts. Subsequently, the ratio-of-ratio and the oxygen saturation were calculated. This approach has the disadvantage that the colour channels have a small bandwidth, which leads to inaccurate results. For that reason, we abandoned the single camera principle.

Consequently, we developed a concept based on two cameras. Two monochrome cameras are placed in a stereo setup with a base distance of 4 cm with optical bandpass filters. The wavelengths of the optical bandpass filters are 660 nm and 940 nm with a full width at half maximum of 50 nm. This is a tradeoff between a small bandwidth with a poor brightness and a large bandwidth, which leads to an inaccurate calculation of the ratio-of-ratios. The images of both cameras are recorded simultaneously by means of a trigger cable.

In our measurements, we had the goal to determine the oxygen saturation on the arm. To that goal, at first, a foreground segmentation was carried out to separate foreground and background. An ROI is placed in the foreground, i. e. the arm. Subsequently, minimum Eigenvalue features (Shi and Tomasi, 1993) are detected and tracked with a KLT-tracker (Tomasi and Kanade, 1991) in the video sequence. In the next step, for each corresponding image pair, a feature matching is carried out. This guarantees that the same ROI is considered in both images. For both ROIs one time channel can be extracted by averaging the pixels within the ROIs.

By shifting a sliding window over the time channels, the AC- and DC-parts can be computed. Hereby, the DC value is equivalent to the mean value within the sliding window. The gap between minimum and maximum value in the windows represents the AC value. The ratio-of-ratio is calculated as follows:

$$R(\phi) = \frac{\frac{AC_{660nm}(\phi)}{DC_{660nm}(\phi)}}{\frac{AC_{940nm}(\phi)}{DC_{940nm}(\phi)}} \tag{1}$$

Thereby, R denotes the ratio-of-ratios and ϕ the current window. Thereupon, the oxygen saturation SpO_2 can be determined.

$$SpO_2 = A - B \cdot R \tag{2}$$

Hereby, A and B stand for the calibration parameters, which have to be determined during calibration.

4.3 Results and Discussion

In order to evaluate the performance of the proposed algorithm, videos of five different probands were recorded. All probands were healthy and had an oxygen saturation of 98-99 %. Due to the fact, that this small range is not sufficient to perform a linear approximation between ratio-of-ratios and oxygen saturation, the probands had to hold their breath, which results in a decrease of the oxygen saturation down to 92 % at minimum. A lower value would only be possible for ill persons with a decreased oxygen saturation.

The measurements were carried out by two Basler A640gm monochrome cameras with disabled automatic white balance and disabled automatic exposure time control. As reference system, a Pulox Po200 pulsoximeter was used during the measurements.

The results indicate that there is a linear dependency between the ratio-of-ratios and the reference oxygen saturation. However, a robust determination of the calibration parameters A and B is not possible for our sequences. There are large individual differences between the single subjects. Therefore, a usage in home environments is impossible at the moment, so that further work has to be carried out.

However, there is a huge potential for using a remote oxygen determination system. Current systems, such as the pulsoximeter, only provide information about the oxygen saturation on a certain body part, e. g. the finger. Under utilisation of an image-based system, an oxygen saturation map on the skin is feasible. With such a map, it is possible to detect local deviations of the oxygen saturation in certain body parts. That would be a strong indicator for abnormalities and diseases.

5 REMOTE BLOOD PRESSURE DETERMINATION

5.1 Related Work

Measuring the blood pressure remotely is the most recent research topic in the field of vital parameters and is based on the methods of remote heart rate determination. Normally, the blood pressure is measured by means of a blood pressure cuff. This procedure is non-invasive but not remote.

Murakami et al. proposed to use the pulse transit time (PPT) between signals extracted from a hand and a foot ROI (Murakami et al., 2015). They used the green channel and filtered this channel to obtain the PTT. The blood pressure can be determined because of its linear relationship to the PTT. In a similar way, Jeong et al. (Jeong and Finkelstein, 2016) and Secerbegood et al. (Secerbegovic et al., 2016) calculated the heart rate but used a face and a hand region. In comparison to that, Sugita et al. suggested to determine the ROIs of the right palm, the forehead and the left cheek manually and calculate the phase difference between the two signals by using the Hilbert transform (Sugita et al., 2015).

Although the related works demonstrated an experimental feasibility, more work has to be carried out.

5.2 Proposed Method

A direct determination of the blood pressure by means of the magnitude of the time-varying signal is impossible because of the variety of influencing factors, such as lighting, exposure time, gain factor or individual differences of the vessels.

Hence, an indirect method is advantageous. There is a linear relationship between the blood pressure (BP) and the pulse wave velocity (PWV). The higher the PWV, the higher is the blood pressure. This can be modelled by the following equation:

$$\mathrm{BP} = a \cdot \mathrm{PWV} + b \tag{3}$$

Hereby, a and b denote individual factors, which have to determined by calibration. The PWV can be obtained by measuring the time t_{Arm} that a pulse wave needs to pass the distance s_{Arm} between two known ROIs.

In order to obtain the PWV, the ROIs have to be determined on the arm. Furthermore, the distance between the two ROIs has to be measured. Currently, this is done manually but should be automatised in future. For the detection and tracking of features, we use minimum Eigenvalue features and a KLT tracking. This is done to reduce the influence of motion artefacts.

A time signal is extracted within a single ROI by averaging all its pixel. By detecting identical peaks of the two regions, the transit time can be calculated. Hereby, the frame rate has to be high enough to detect the peaks and to determine the time difference accurately.

5.3 Results and Discussion

For the evaluation, the probands have to sit still and should not move. A Basler acA640-100gc RGB camera is placed in 0.5 m distance to the subject's right arm. The frame rate is fixed to 50 frames per second.

For reference measurements, a boso medicus X blood pressure cuff is used. Due to the fact that a measurement with the reference system will influence a camera based system, a synchronous measurement is not sensible. Therefore, the blood pressure is determined with the reference system directly before and after the image recording. If both values do not vary too much, the recording is considered as relevant. Otherwise, it is rejected. The probands had to rest at least 10 min before the measurement starts to guarantee a stable blood pressure.

First measurements in the lab proved the linear correlation between blood pressure and PWV. However, more work has to be carried out to reduce the influence of individual differences. An utilisation in home environments is not given at the moment.

Nevertheless, this image-based method has some advantages in comparison to the conventional method. For patients who have to measure their blood pressure regularly (e. g. automatic measurement every 15 or 30 min), a contact-less method provides considerably more comfort. Furthermore, from a medical point of view it is relevant, to determine the blood pressure on different body parts and not only on one arm. If the PWV is smaller only in one limb, this can be an indicator for peripheral arterial diseases.

6 CONCLUSIONS

In our work we evaluated the vital parameters heart rate, respiration rate, oxygen saturation and blood pressure concerning their remote, image-based determination in home environments. The results are summarised in Table 3. The heart rate and the respiration rate can be determined accurately and can be deployed in the field of home environments. The methods to determine the oxygen saturation and the blood pressure have to be made more robust before evaluating them in real world scenarios.

Table 3: Availability of remote vital parameter determination in home environments.

Vital parameter	Availability
Heart rate	Ready for usage in the field
Respiration rate	Ready for usage in the field
Oxygen saturation	Improvements necessary
Blood pressure	Improvements necessary

Next to the field of home environments, remote vital parameter determination can be beneficial in other fields as well. Possible application fields are the prevention of sudden infant death syndrome, sleep monitoring, monitoring of a driver's well being, monitoring of training in rehabilitation centres and triage in hospitals.

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